Journal of KOSSE. (2020. 12) Vol. 16, No. 2 pp. 97-109
DOI: https://doi.org/10.14248/JKOSSE.2020.16.2.097
www.kosse.or.kr

ISSN (print) : 1738-480X
ISSN (online) : 2288-3592

A Systems Engineering Approach to Predict the Success Window of FLEX Strategy under Extended SBO Using Artificial Intelligence

Salama Obaid Alketbi[1)], Aya Diab[1),2)*]

1) Nuclear Engineering Department, KEPCO International Nuclear Graduate School, Ulsan, South Korea,

2) Mechanical Power Engineering Department, Faculty of Engineering, Ain Shams University, Cairo, Egypt.

Abstract : On March 11, 2011, an earthquake followed by a tsunami caused an extended station blackout (SBO) at the Fukushima Dai-ichi NPP Units. The accident was initiated by a total loss of both onsite and offsite electrical power resulting in the loss of the ultimate heat sink for several days, and a consequent core melt in some units where proper mitigation strategies could not be implemented in a timely fashion. To enhance the plant's coping capability, the Diverse and Flexible Strategies (FLEX) were proposed to append the Emergency Operation Procedures (EOPs) by relying on portable equipment as an additional line of defense. To assess the success window of FLEX strategies, all sources of uncertainties need to be considered, using a physics-based model or system code. This necessitates conducting a large number of simulations to reflect all potential variations in initial, boundary, and design conditions as well as thermophysical properties, empirical models, and scenario uncertainties. Alternatively, data-driven models may provide a fast tool to predict the success window of FLEX strategies given the underlying uncertainties. This paper explores the applicability of Artificial Intelligence (AI) to identify the success window of FLEX strategy for extended SBO. The developed model can be trained and validated using data produced by the lumped parameter thermal-hydraulic code, MARS-KS, as best estimate system code loosely coupled with Dakota for uncertainty quantification. A Systems Engineering (SE) approach is used to plan and manage the process of using AI to predict the success window of FLEX strategies under extended SBO conditions.

Key Words : Systems Engineering, APR1400, FLEX Strategies, Emergency Operation Procedures, Modeling and Simulation, Extended SBO, Artificial Intelligence, MARS-KS, Peak Cladding Temperature (PCT), SAMG, Best Estimate Plus Uncertainty (BEPU), Artificial Neural Network (ANN), V-Model.

Received: October 13, 2020 / **Revised**: November 18, 2020 / **Accepted**: November 24, 2020

* 교신저자 : Aya Diab, aya.diab@kings.ac.kr, aya.diab@eng.asu.edu.eg

1. Introduction

For an extended station blackout (SBO) scenario, when all power sources are lost, the main feedwater MFW pumps will be lost too, but turbine-driven auxiliary feedwater pumps (TDAFWPs) will take over for 8 hours until DC battery depletion. At which point, the secondary side heat sink will be lost and the plant undergoes a severe accident unless the FLEX strategies are implemented. To prevent the nuclear plant from undergoing a severe accident, operators should strictly follow appropriate emergency operation procedures (EOPs) given that all plant safety systems work as expected.

Additionally, the FLEX strategy which involves the deployment of portable equipment may be implemented to provide core cooling. The FLEX strategy is considered to fail when the peak cladding temperature (PCT) exceeds 1477 K. Assessing the success window of the implementation of the FLEX strategy can be achieved via deterministic safety analysis using the best estimate plus uncertainty methodology, which may be time-consuming. It may also be assessed using data-driven models as a computationally efficient alternative.

This work explores the use of the latter approach to identify the success window of FLEX strategy implementation under extended SBO conditions.

To achieve this goal, the Systems Engineering (SE) approach is adopted to plan and manage the application of Artificial Intelligence (AI) using an artificial neural network (ANN) to predict the plant response to an extended SBO.

To train the ANN model, a dataset is generated using a thermal-hydraulic model. The database uses the maximum core temperature, PCT, as a metric for the plant response to evaluate the effectiveness of the implemented strategy as a function of key system parameters.

This work builds on a previous work (Ricardo and Diab 2019) where the Best Estimate Plus Uncertainty (BEPU) approach is implemented to ensure that key uncertainties are considered.

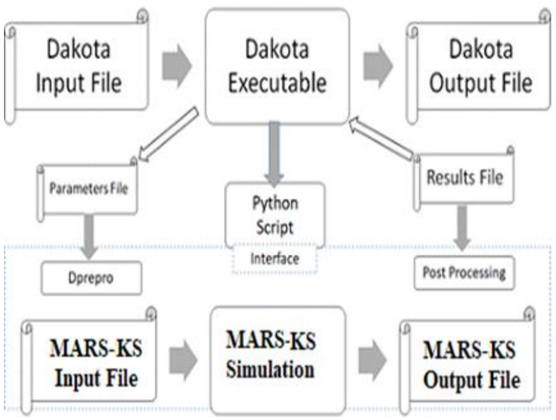
2. Methodology

The methodology followed in this paper can be divided into two main sub-sections. The first section describes the thermal-hydraulic model and the second section describes the artificial neural network model.

2.1 TH Model Development

The first step is to develop a thermal-hydraulic model of APR 1400 under SBO scenario. In order to create a dataset for training and validation of the AI algorithm, a thermal-hydraulics model was developed to assess the impact of the uncertainty parameters on the PCT which is used as a success criterion of the FLEX strategy. This is achieved by coupling the thermal-hydraulic code, MARS-KS to the statistical tool, Dakota, using Python programming language to provide the communication interface as shown in Figure.1. MARS-KS V1.4 is used to model the fluid behavior, reactor kinetics, and heat transfer, while Dakota is used to propagate the input parameters including underlying uncertainties throughout the thermal-hydraulic model.

The uncertainty analysis is performed using a set of uncertain parameters derived from key phenomena that govern the accident progression as identified in previous studies (Kang et al., 2013). This thermal-hydraulic model is used to create the dataset that will be used to train the AI model.

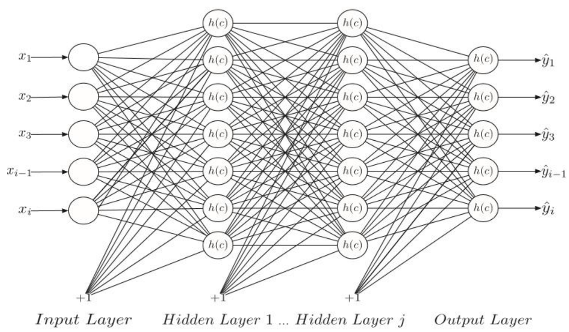


[Figure 1] Uncertainty Analysis Framework

2.2 AI Model Development

The utilization of AI in the field of nuclear safety has been limited, despite the proven advantages of fast and accurate prediction which makes it an area worthwhile for further research (Mario et al., 2017). In this work, the developed AI algorithm utilizes the ANN technique. The ANN is used to model the mathematical relationship between the inputs and output via a set of artificial neurons that are interconnected by weights and biases. During the training phase, these weights and biases are adjusted to reflect the salient relationship between inputs and outputs, hence predict the outputs. As shown in Figure. 2 the ANN has three types of layers, an input layer, a hidden layer, and an output layer.

The network involves an input layer that contains the input signal, an output layer that generates the output of the network, and a hidden layer that performs the nonlinear transformations of the input to reflect the complex and usually nonlinear mathematical relationship between the input and output. For the case at hand, the ANN algorithm acts as a classifier, going through the database to identify the successful implementation of FLEX strategy given a certain set of initial, and operating conditions.



[Figure 2] Neural Network Representation

3. Systems Engineering Approach

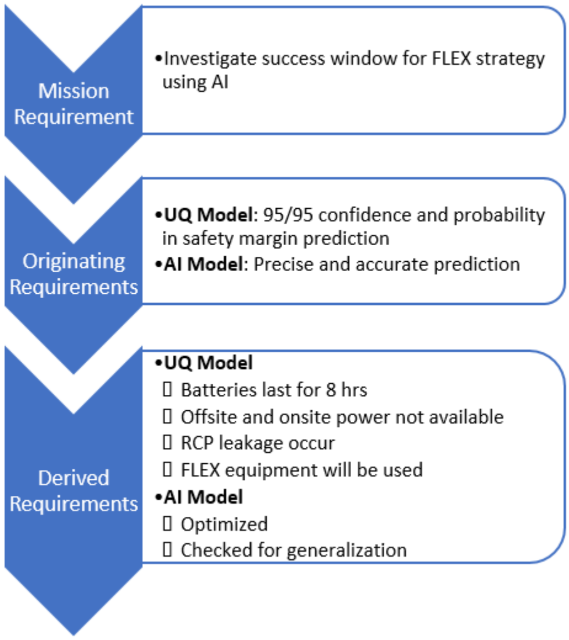
A SE approach is used in this study to plan and manage the development of the process of the AI algorithm, with verification and validation tests conducted at every phase of development to ensure that all requirements are met within satisfactory limits. The V-Model, shown in Figure. 4, illustrates a set of verification and validation activities that guides this work development by linking each requirement to a validation or verification test with predefined success criteria. The V-model provides a holistic understanding of the whole process with integrated systems requirements that streamlines the work, reduces the errors and expedites the process.

3.1 Requirement Analysis

During the project design phase, the requirement analysis was conducted to identify the mission of this research which is developing an AI algorithm to predict the success window of FLEX strategy to prevent the system from undergoing a severe accident based on the success criteria explained earlier. As illustrated in Figure. 3 the first originating requirement for this mission is utilizing the Uncertainty Quantification model to produce a dataset that satisfies the regulatory requirement for safety margin prediction with 95% probability and 95% confidence level. The second originating requirement is to develop an AI Model that predicts accurately and precisely the FLEX success window using the dataset. The derived requirements are training and optimizing the AI Model then deploy it and test it for generalization.

3.2 System Design Phase

In this phase, the AI model will be developed to predict the success of the FLEX strategy. This model will be trained using a pre-existing database generated using the thermal-hydraulic model, and subsequently tested by comparing its prediction with the output predefined by the database.



[Figure 3] Requirement Analysis

The originating requirement is the development of the model that shall predict whether the mitigation strategy succeeds for various initial and operating conditions. The model shall perform robustly, quickly, and accurately solely based on the database and not the physics-based model. Therefore, once developed, the model shall obtain the prediction faster than the conventional deterministic methods. Additionally, the model shall be able to process big size data with reasonable accuracy and generalization.

3.3. Architectural Design

When it comes to system architecture, two codes (MARS-KS and Dakota) are loosely coupled using Python programming language to provide the two-way communication interface as shown in Figure. 5. This process requires generating a big dataset to train the AI algorithm to perform well.

3.3.1 Accident Scenario

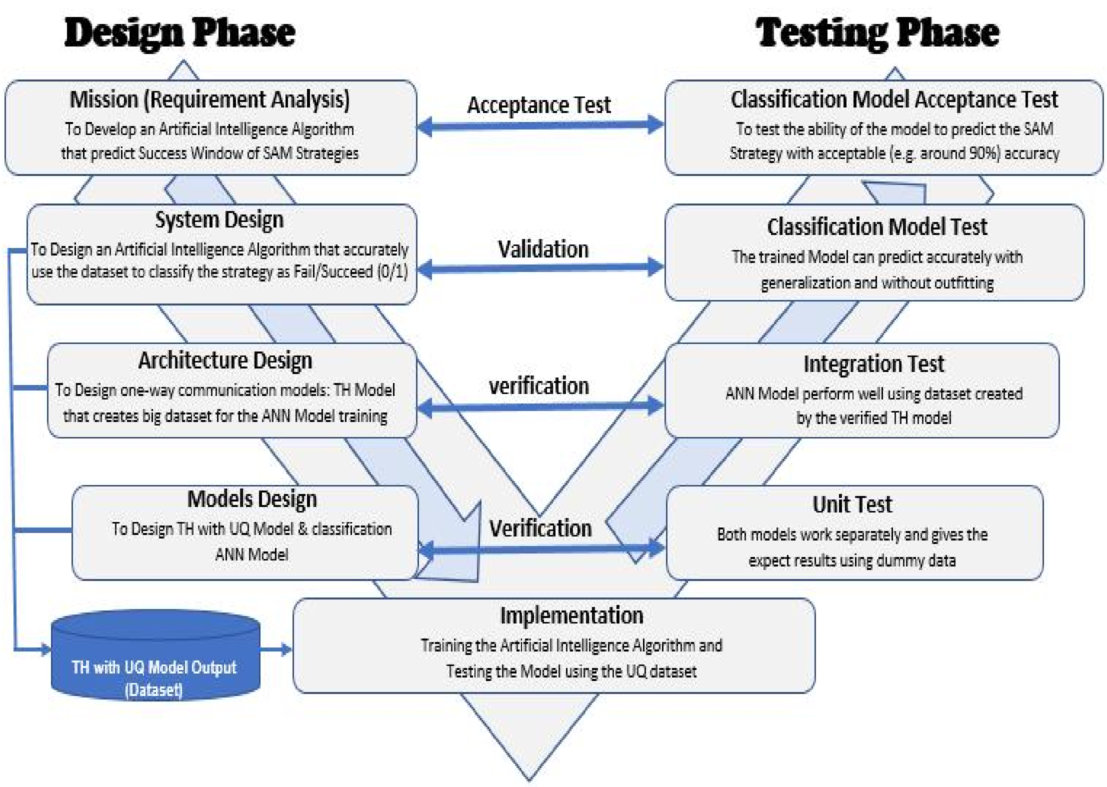
Selecting the accident scenario is an essential step to identify the functional and physical architecture which will be considered in the development of an extended SBO for APR1400 thermal−hydraulic model as illustrated in Figure. 6.

3.3.1.1 Constraints and Assumptions

The derived requirements include the systems and components requirements which impose limits and constraints. For the extended SBO scenario, the AC power and emergency diesel generators shall not be available, i.e. all motor−driven pumps shall not be available. The battery should provide power for up to 8 hours only then the FLEX equipment should be used, assuming they are aligned at 2 hours. The operator shall provide feed and bleed operation to remove the decay heat, the reactor coolant pump (RCP) seal leakage is expected to occur due to loss of component cooling water pump, and any operator action is given 30 minutes. The maximum shutoff head of the primary mobile pump shall be 1.223 MPa while the maximum shutoff head of the secondary mobile pump shall be 0.223 MPa. All these limits and constraints are considered in the thermal−hydraulic model development.

3.3.1.2 Nodalization

The main systems and components of the APR 1400 plant are listed in Table 1. The plant is represented using the simplified nodalization shown in Figure. 7, where the



[Figure 4] V−Model

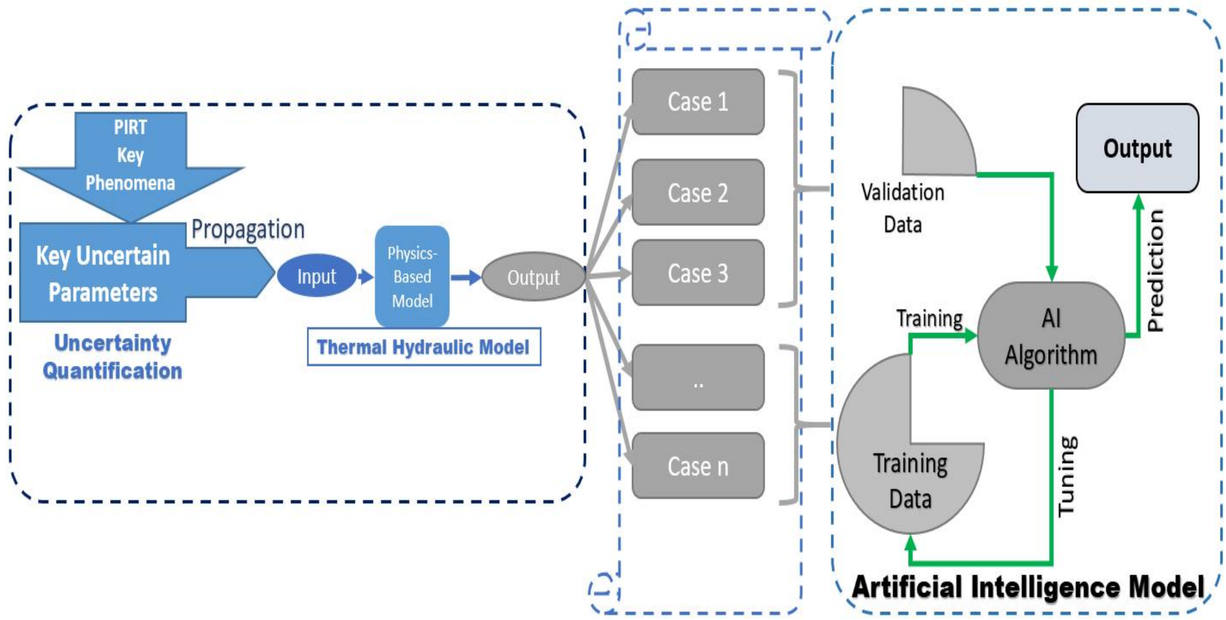
turbine and containment are represented each as a boundary condition using time-dependent volumes.

<Table 1> APR 1400 Systems and components

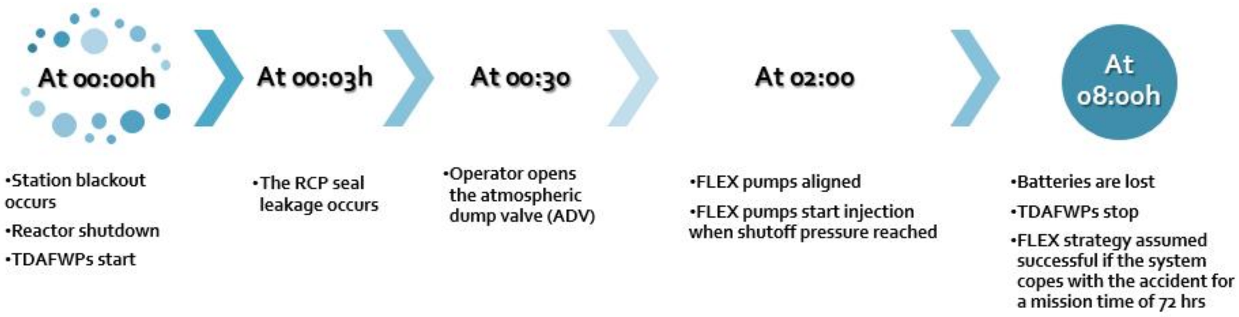
Reactor Coolant System (RCS)
Reactor Pressure Vessel (RPV)
2 Hot Legs
4 Cold Legs and four Reactor Coolant Pumps (RCPs)
Pressurizer (PZ)
Pressurizer Safety relief Valves (PRSVs)
Safety Depressurization System (SDS)
Secondary System
2 Steam Generators (SGs)
Main Feedwater System (MFWS)
Main Steam Line (MSL)
6 Secondary Main Steam Safety Valves (MSSVs)
2 Main Steam Line Atmospheric Depressurization Valves (MSL-ADVs)
2 Main Steam Line Isolation Valves (MSLIVs)
Turbine Bypass Valve (TBV)

3.3.2 Functional Architecture

The functional architecture describes the main functions that need to be executed to prevent the plant from undergoing a severe accident. The most important function is to maintain core cooling by establishing and maintaining natural circulation. This is achieved by providing water to the steam generators (SGs) and establishing a flow path on the secondary side by opening the



[Figure 5] Architectural Design

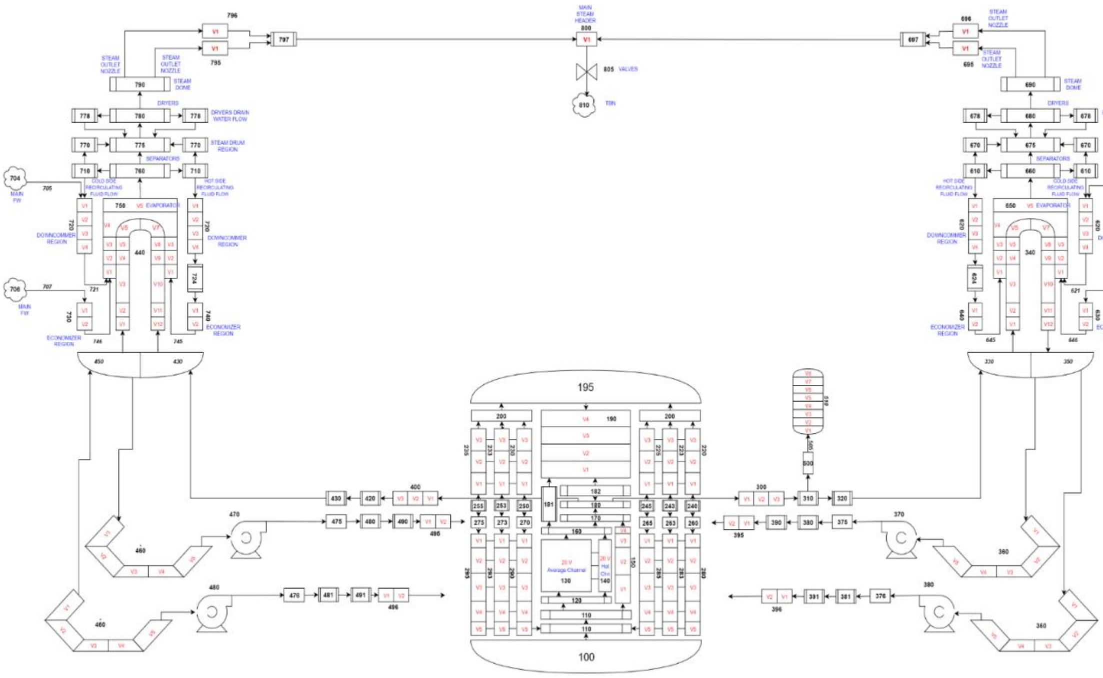


[Figure 6] Accident Scenario

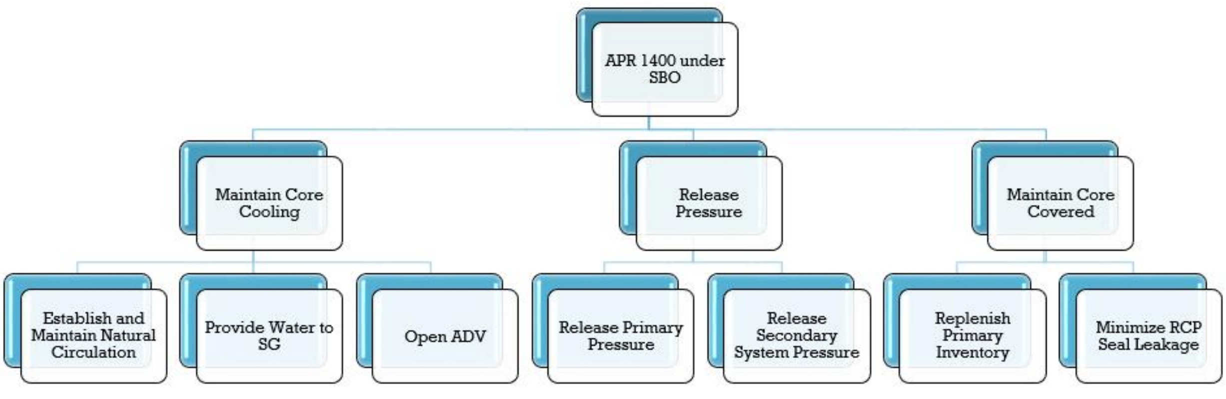
atmospheric dump valves (ADVs).

Depressurization is another function that can be achieved by releasing the primary system pressure and the secondary system pressure to enable the safety injection and/or external injections. Furthermore, core coverage should be ensured by maintaining the RCS inventory by providing water to the primary system as illustrated in Fig.8.

While the functional architecture for the AI model describes the training, validation, and model deployment. The dataset generated by the thermal-hydraulic model and used for the AI algorithm development is divided into two sets one for training the algorithm and the other for testing it. Once developed, the model can be used as a predictive tool. The functional architecture for the AI model



[Figure 7] MARS-KS Nodalization



[Figure 8] APR 1400 Extended SBO Functional Architecture involves processing the dataset according to four main steps. Preprocessing is the first step and involves data cleaning, zero centering, and normalization of the data. The second step is the model development which includes the number and shape of layers, number of neurons per layer, model training, optimization of network structure and topology, and tuning the model hyper-parameters. The third and fourth steps are the validation then deployment of the model for prediction.

3.3.3 Physical Architecture

Physical architecture represents the main systems and components available under SBO condition which are linked to the functional architecture. The main components that will be included in the APR 1400 model under extended SBO are the RCP, safety injection tank (SIT), FLEX portable pump for injection into the core, and the pilot-operated safety release valves (POSRVs) for depressurization of the primary side. For the secondary side, the main components include the SGs, TDAFWPs, and ADVs for cooling and depressurization, the main steam safety valves (MSSVs) for secondary system pressure relief, and depressurization as well as the FLEX portable pumps for water injection into the SGs.

Regarding the physical architecture the AI model, shown in Figure.2, illustrates the ANN which consists of an input layer, a number of hidden layers, and an output layer. The ANN architecture is established after a series of trials to reach the most compact and computationally efficient network that can capture the salient features imbedded in the dataset with fast convergence and sufficient generalization. This can be achieved by optimizing the network hyperparameters, i.e. the activation functions weights and biases, the ANN structure and topology including network shape, number of hidden layers, and number of nodes in each layer. This was achieved using the TALOS optimization tool. Additionally, the fraction of the dataset used for training and testing can be manipulated during the model optimization process.

3.4 Module Development Phase

This phase involves the development of the thermal-hydraulic (TH) model and the AI model. The TH model shall correctly simulate the plant response. The AI model shall be developed to accurately classify the plant response correctly for the various input parameters.

The requirement for this phase is to generate an accurate and big size dataset from the verified and validated base case accident simulation. The AI algorithm shall be able to process the data and train the model to classify the output with reasonable accuracy.

3.5 Implementation Phase

The implementation phase starts by preprocessing the dataset created by the TH model by cleaning, zero-centering, normalizing, and splitting the dataset into a training dataset and a testing dataset. The next step is developing the AI model by using the training dataset to train the ANN. After that, the trained model shall be validated using the test dataset. Once the trained model is validated, it shall be able to classify the success window of the FLEX strategy based on the plant response for a given combination of initial conditions and operation parameters.

3.6 Verification and Validation Phase

The purpose of verification is to make sure that the designed and built systems meet the requirements specified during the design development stage, while the purpose of validation is to ensure that the given outcome is matching the mission requirements (Ryan et. al., 2017). The verification process is implemented at the unit and integrated model levels. In the unit test, both models shall be verified to check if they perform well independently and each gives the expected output using dummy data. While in the integration test, the AI model shall perform well with the dataset generated by the TH model which correctly reflects the plant response using a qualified model of the plant. In the system validation test, the AI model shall be checked for overfitting and generalization. The AI model is acceptable if it is capable of predicting the FLEX success window with the required accuracy.

The model accuracy and precision can be checked using the confusion matrix (CM). The CM describes the performance of a classification model on a set of test data, for which the true values are known. For binary class problems, there are 4 performance metrics, on the one hand: true positive and true negative (TP and TN) and on the other hand: false positive and false negative (FP and FN). From these 4 metrics, 4 types of scores can be generated that determine the prediction accuracy, precision, recall, and F1 score (Gharam et. al., 2020).

The prediction accuracy is the sum of true positive and true negative divided by both true and false positive (TP, FP) and true and false negative (TN, FN). Accuracy, therefore, indicates the ratio of correctly predicted observation to the total observations and can be calculated as follows:

$$\frac{TP+TN}{TP+TN+FP+FN}$$

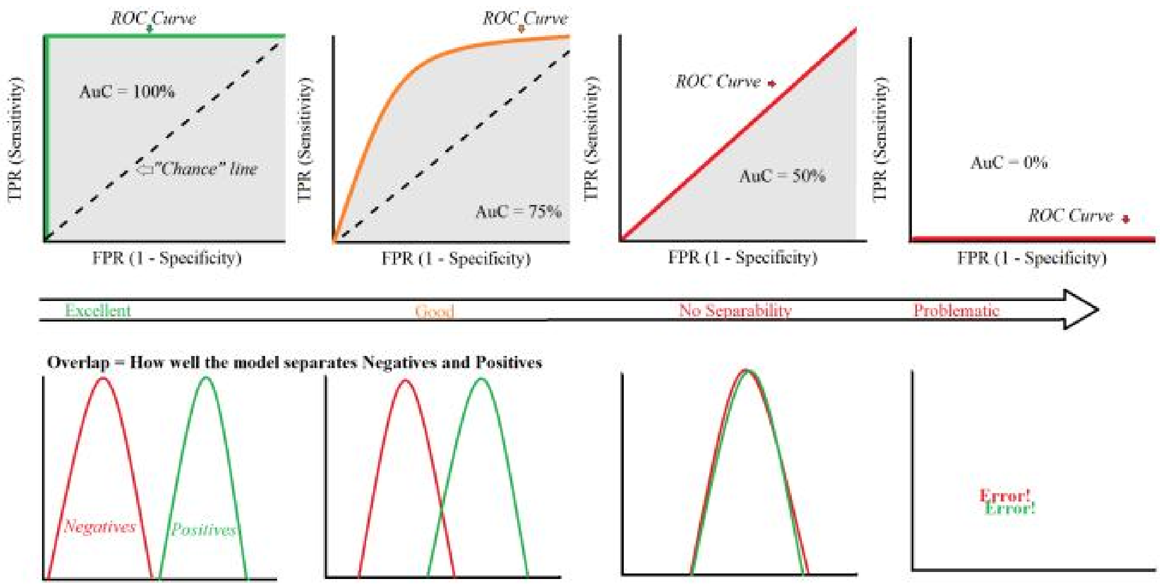
It is worth noting that accuracy is not the right metric to evaluate the prediction in case of class-imbalance problem, where the subset of the database representing one class is much smaller than that representing the other class. The metrics precision and recall are recommended for this kind of problem. Precision represents the fraction of correctly predicted positive observations to the total predicted positive observations and has therefore to be as high as possible. Precision can be calculated as follows:

$$\frac{TP}{TP+FP}$$

F1 score takes both false positives and false negatives into account via a weighted average of both Precision and Recall:

$$F1 = 2\ \frac{Precision\ \ Recall}{Precision + Recall}$$

Its value ranges from 0 to 1 and the higher



[Figure 9] Receiver Operator Curve (ROC) and Area Under the Curve (AUC).

its value the better the classifier. In fact, F1 is a more useful indicator than accuracy, especially with uneven class distribution. Accuracy works best if false positives and false negatives have a similar cost. However, if the cost of false positives and false negatives are very different, it's better to consider the F1 score.

The Receiver Operator Curve (ROC) and Area Under the Curve (AUC) are very important metrics to evaluate the model prediction capability. ROC is a graph showing the performance of a classification model at all classification thresholds. It pictorially compares the True Positive Rate (TPR) which represents the model sensitivity to the False Positive Rate (FPR) which represents the model specificity. The AUC represents the degree to which the model can separate the different classes. The AUC of the ROC should therefore be close to 1. Considering Figure. 9, the ROC shall be as far as possible from the dotted line if the model is to have a good prediction capability and have a high AUC.

3.6.1 Unit Testing

In the unit test, the performance of both models shall be verified separately to make sure that they can predict the expected output using a dummy dataset. To verify the AI model, it shall be trained using a dummy dataset to verify that the algorithm is working properly. And to verify the behavior of the components inside the simulation module of the SBO accident scenario, the steady state response shall be compared with the corresponding values reported in the DCD. Additionally, the model predictions for the plant transient response shall be compared with previous research papers and the uncertain parameters shall be checked for independency. Both models shall be tested and shall work well separately.

3.6.2 Integration Testing

In the integration test, the AI model shall perform well with the dataset generated by the TH model which correctly reflects the plant response for a qualified model of the plant. The AI model shall perform well in classifying the FLEX success window when trained using the verified dataset generated by the TH Model. To verify the model performance, the prediction shall be checked and evaluated using the Recall value which indicates how well the model predicts the already known class based on the pre-existing database.

3.6.3 System Testing

In system validation test, the AI model shall be checked for overfitting and generalization. The trained AI model prediction shall be verified using the testing subset of the database with acceptable accuracy while avoiding overfitting. Overfitting can be identified by comparing the training and validation accuracy, if the training accuracy is higher than the validation accuracy, then the model suffers from overfitting.

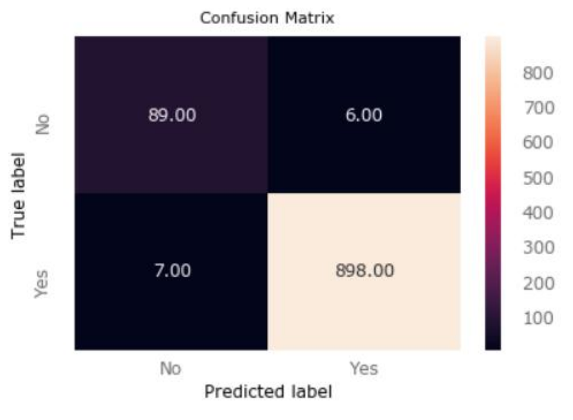
3.6.4 Acceptance Testing

This test emphasizes that the model should predict the success window of the FLEX strategy accurately and with enough generalization. The model is considered acceptable if the predictions are matching the predefined outputs in the testing subset of the database (unseen dataset) with an accuracy of around 95.4%, which confirms the generalization of the model.

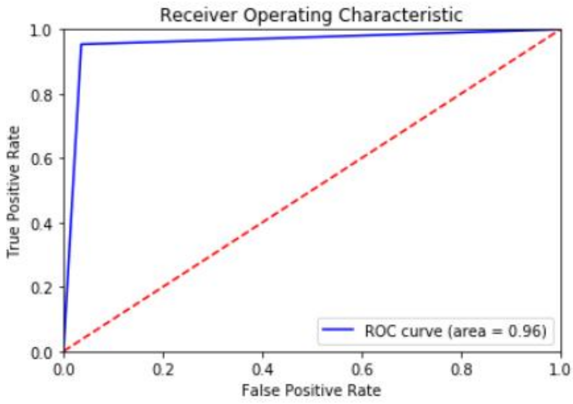
4. Results

Once the ANN has been developed through training, validation, and optimization process it can now be used to predict the classification of different scenarios of extended SBO accident using various initial and operating conditions (features) to reflect the spread of uncertain parameters. Figure. 10 illustrates the distribution of TP, TN, FP, and FN as predicted by the trained model. Out of 954 success cases, the model predicts correctly 927 cases of successful implementation of the FLEX strategy. Clearly, the model can predict the success window with an acceptable accuracy of 95.4%, a precision of 99%, a Recall of 97%, and an F1 score of 0.49%. However, for uneven classes distribution the best indicator is F1 score and in this case F1 score is low. This result means that failed cases are predicted with a much lower accuracy because the dataset representing the failed cases in the original database is relatively small.

Figure. 11 shows that the AUC of the ROC is 0.96, i.e. very close to 1, which means that the prediction capability is considered very well.



[Figure 10] Confusion Matrix



[Figure 11] Model ROC Curve and AUC

6. Conclusion

The SE approach has been adopted to plan and manage the current work. The V-model provided a useful tool by ensuring that the requirements are met at each phase of the project development.

A TH model with uncertainty quantification of the plant response under extended SBO was developed to create the database for the AI algorithm. Once the AI algorithm was successfully developed and trained, it was used to predict the PCT of an unseen subset of the database.

Although the development of the AI algorithm is time-consuming; but once developed, the prediction can be obtained much faster than conventional deterministic methods. This may be particularly useful in expediting the decision-making process under severe accident conditions. This is the focus of an ongoing research effort that is being conducted in parallel to this work.

Acknowledgement

This research was supported by the 2020 Research Fund of KEPCO International Nuclear Graduate School (KINGS), Republic of Korea.

References

1. INCOSE (2015) Systems Engineering Handbook. 4th Edition, Edited by T. M. S. David D. Walden, Garry J. Roedler, Kevin J. Forsberg, R. Douglas Hamelin. Hoboken, New Jersey.
2. J. Ricardo Tavares de Sousa, Aya Diab "Best Estimate Plus Uncertainty Analysis for SBO", Presented at the 2019 ANS Winter Meeting and Expo, 2019.
3. Lee, S. W., Hong, T. H., Seo, M. R., Lee, Y. S., & Kim, H. T. (2014). Extended station blackout coping capabilities of APR1400. Science and Technology of Nuclear Installations, 2014.
4. T.V. Santosh, et al., "Diagnostic system for identification of accident scenarios in nuclear power plants using artificial neural networks," Reliability Engineering and System Safety, vol. 94, pp. 759-762, 2009.
5. Vinod, S. G., Babar, A., Kushwaha, H., Raj, V. V. (2003). Symptom-based diagnostic system for nuclear power plant operations using artificial neural networks. Reliability Engineering and System Safety, 82(1), 33-40.
6. Saghafi, M., Ghofrani, M. B. (2016). Accident management support tools in nuclear power plants: A post-Fukushima review. Progress in Nuclear Energy, 92, 1-14.
7. Fernandez, M. G., Tokuhiro, A., Welter, K., and; Wu, Q. (2017). Nuclear energy system's

behavior and decision-making using machine learning. Nuclear Engineering and Design, 324, 27-34.

8. Gharam, D. (2020). Machine Learning analysis of text in a Clinical Decision Support System,

9. Ryan, M. J., & Wheatcraft, L. S. (2017). On the Use of the Terms Verification and Validation. INCOSE International Symposium, 27(1), 1277-1290.